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A Geographic Approach to Racial Profiling: The Microanalysis and Macroanalysis of Racial Disparity in Traffic Stops

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ABSTRACT

Despite numerous studies explaining racial disparity in traffic stops, the effects of spatial characteristics in patrolling areas have not been widely examined. In this article, the authors analyzed traffic stop data at both micro- and macro- levels. The micro-level analysis of individual stops confirmed racial disparity in the frequency of traffic stops as well as in subsequent police treatments. Blacks were overrepresented and other racial/ethnic groups were underrepresented in traffic stops, with a greater disparity in investigatory stops. The macro-level analysis found that the likelihood of being stopped and being subjected to unfavorable police treatment (e.g. arrest, search, and felony charge) was greater in beats where more blacks or Hispanics resided and/or more police force was deployed, consistent with the “racial threat” or “minority threat” hypothesis. These findings imply that racial disparity at the level of individual stops may be substantially explained by differential policing strategies adopted for different areas based on who resides in those areas.

ARTICLE

Racial profiling is one of the most discussed issues in policing (Weitzer and Tuch, 2006). Racial profiling occurs when “a person is treated as a suspect because of his or her race, ethnicity, nationality or religion” (American Civil Liberties Union, 2007). It can occur when police officers stop, question, search, investigate, arrest, and/or use some degree of force against a person based on race rather than suspicious or criminal behavior (Harris, 1997; Weitzer and Tuch, 2002). A

well-known form of racial profiling is referred to as “driving while black” or “driving while brown” (DWB).¹

Most American citizens believe racial profiling not only exists but is widespread. For example, a 2003 Gallup Poll showed that 59% of Americans thought police profiling was widespread, including 85% of blacks (Ludwig, 2003). Historical analyses (Skolnick, 2007) and scholarly reviews of the literature (del Carmen, 2007) verify the realities of racial profiling by some police, at some times, in some places. Discrimination that occurs in some places and some time periods is referred to as “contextual discrimination” (Walker, Spohn, and Delone, 2006).

The American Civil Liberties Union (ACLU) has documented evidence of racial profiling in several states, including Arizona, California, New York, Ohio, and Rhode Island. It also has led efforts to file complaints against police departments in cities in other states (ACLU, 2007). Amnesty International also has investigated racial profiling (Amnesty International, 2007). According to Amnesty, 32 million Americans “report they have already been victims of racial profiling.” Further, about 87 million Americans “are at a high risk of being subjected to future racial profiling during their lifetime.”

When it occurs, racial profiling has dramatic negative effects on those targeted, including emotions such as fear, frustration, depression, and anger (Birzer and Smith-Mahdi, 2006; Hart et al., 2003). Further, racial profiling hurts law enforcement efforts since it hinders trust between the police and community. Racial profiling has also been shown to be largely ineffective with regard to the wars on crime, drugs, and terrorism (Robinson, 2005).

The current study examines traffic stop data at both micro- and macro- levels in order to assess the likelihood of racial profiling in Houston, Texas. At the micro-level, we analyze racial discrepancies in traffic stops in terms of the likelihood of being stopped and the types of police

treatments after stops. At the macro-level, we examine the spatial distribution of traffic stops and stop outcomes, especially focusing on how racial disparities in traffic stops are associated with characteristics of police beats.

The macro-level of analysis is important to fully understand racial profiling because police agencies do not utilize the same crime control strategies in different areas within their jurisdictions; deployment of police force varies geographically depending upon the demand for patrol resources. In general, more patrols are allotted to communities that generate a greater number of calls for service and host higher rates of reported crime (Doerner, 1997). Differential crime control approaches, supported by problem-oriented policing strategies and “hot spot” analyses, are considered by police administrators as appropriate means to utilize limited police resources (Paulsen and Robinson, 2004). Further, the macro-level is also important because police officers tend to be disproportionately assigned to minority communities, a phenomenon supposedly owing itself to a perceived threat posed by members of certain racial minority groups (Holmes, 2000; Parker, Stults, and Rice, 2005; Stolzenberg, D’Alessio, and Eitle, 2004; Stults and Baumer, 2007).

LITERATURE REVIEW

In this review, we outline the many studies that have found evidence of racial profiling. We also discuss those studies that have not found evidence of racial profiling. The goal is to provide some context for our study of racial profiling in Houston, Texas.

Typically, studies of racial profiling illustrate that blacks and other racial minorities are more likely than whites to be stopped; that they are especially more likely to be stopped for minor traffic violations as well as for non-driving traffic violations such as vehicle defects, license/registration checks, and other traffic offenses; that they are more likely to be searched

after being stopped; and in some cases they are more likely to be ticketed and/or arrested (Barlow and Barlow, 2002; Batton and Kadleck, 2004; Bostaph, 2007; Buerger and Farrell, 2002; Engel and Calnon, 2004; Gross and Barnes, 2002; Harris, 1999; Lamberth, 1997; Langan et al., 2001; Lundman, 2004; Meehan and Ponder, 2002; Peruche and Plant, 2006; Petrocelli, Piquero, and Smith, 2003; Romero, 2006; Schafer et al., 2006; Tomaskovic-Devey et al., 2006; Warren et al., 2006).

However, other studies have not found evidence of racial profiling (Novak, 2004; Smith and Petrocelli, 2001). Further, some studies raise the possibility that minorities may be more involved in criminality (Gaines, 2006), some drug crimes (Lichtenberg, 2006), and speeding offenses (Lange, Johnson, and Voas, 2005), thereby justifying higher stop and arrest rates by police of some groups.

Among the most well known studies to find evidence of racial profiling include studies of the New Jersey Turnpike in 1996 by Lamberth Consulting and a follow-up study in 2000. The 1996 study found that blacks accounted for 73% of stops in spite of making up less than 14% of road users. The 2000 study showed that although blacks and Hispanics made up 78% of those searched by officers, contraband was found on whites more than blacks and Hispanics (25%, 13%, and 5%, respectively) (ACLU, 2007). However, a study of New Jersey by Lange Johnson, and Voas (2005) found that one significant reason blacks were more likely to be stopped in the state was because they were overrepresented among speeders. The authors noted, however, that the study did not disprove the racial profiling hypothesis.

A study by the New York State Attorney General in 1999 of the New York City Police Department's "stop and frisk" practices of pedestrians found further evidence suggestive of racial profiling. It found that, although blacks make up just 26% of the population, they accounted for

51% of all the stops during the period of the study. Hispanics, who made up 24% of the population, accounted for 33% of all the stops. Whites, who made up 43% of the population, accounted for only 13% of all stops.

Blacks also were overrepresented among stops by the city's aggressive Street Crime Unit (SCU), as they accounted for 63% of all stops by the SCU. Most telling, even in precincts where blacks and Hispanics made up less than 10% of the population, they accounted for more than half of the total stops in these areas (Office of the New York State Attorney General, 1999).

A study in the state of Massachusetts by the Institute on Race and Justice at Northeastern University also found evidence of possible racial profiling. It determined that across 366 agencies, racial disparities were above average in 141 communities (38% of Massachusetts jurisdictions) (Farrell et al., 2004: 25). After attempting to control for percentages of drivers of each race on the roads, the authors found racial disparities that were above average in 201 communities (56% of jurisdictions) (Farrell et al., 2004: 25-26).

With regard to police searches, the study found that across Massachusetts, white drivers were less likely to be searched than non-white drivers (1.3% versus 1.8%, respectively), and “racial disparity in searches was observed in 208 jurisdictions throughout the state” (Farrell et al., 2004: 26). With regard to citations and warnings the authors found that white drivers were less likely than non-white drivers to receive a citation (66% versus 72%, respectively). According to the authors, “in some communities in Massachusetts officers may be more likely to use their discretion to give written warnings to white drivers rather than to non-white drivers. In fact out of ... 142 communities ... non-white drivers were significantly more likely to receive a citation in 58% or 83 of the communities. While all drivers may be more likely to be cited for egregious violations of the law, differential behavior patterns do not appear to explain away racial

differences in citation and warning rates” (Farrell et al., 2004: 28).

The Illinois Traffic Stop Study, which used a unique methodology, found evidence consistent with racial profiling as well (Weiss and Grumet-Morris, 2006). The authors of the study constructed a ratio based on estimates of the minority driving population compared with the percentage of stops of minorities by agencies. According to the authors, the overall ratio in the state of Illinois was 1.12, meaning minorities were being disproportionately stopped (Weiss and Grumet-Morris, 2006: 3).

The authors found that whites were more likely than minorities to be stopped for moving violations (73% versus 68%, respectively) and that minorities were more likely than whites to be stopped for non-moving violations (32% versus 27%, respectively). According to the authors: “This difference manifests itself more clearly when we observe the distribution of stops for license/registration violations, a non-moving violation. This class of offenses is instructive because law enforcement officers can generally exercise significant discretion in deciding whether to initiate these contacts” (Weiss and Grumet-Morris, 2006: 5).

Clear differences were also found for consent searches. Minorities were nearly 3 times more likely than whites to be subject to a consent search. In 2005, blacks were 3.3 times more likely to be subjected to consent searches than whites and Hispanics were 2.7 times more likely (Weiss and Grumet-Morris, 2006: 6). Finally, minorities were more likely than whites to be cited (68% versus 60%, respectively) (Weiss and Grumet-Morris, 2006: 6).

The Rhode Island Traffic Stop Report found further evidence consistent with racial profiling (Farrell and McDevitt, 2006). Among its key findings were that, after being stopped, non-white drivers were more likely than white drivers to be subjected to a discretionary search (5.9% versus 2.9%, respectively). Further, in “22 of the 39 agencies studied, non-whites [were]

significantly more likely than whites to be subjected to a discretionary search. Statewide, the odds of a non-white motorists being searched [were] roughly twice that of a white driver being searched” (Weiss and Grumet-Morris, 2006: 2). Importantly, in this study, people of color were less likely to be found with contraband than whites.

Studies have also been conducted in numerous other states, as well as specific cities and even within individual police agencies. These include, but are not limited to, Ann Arbor, Michigan, Charlotte, North Carolina, Eugene, Oregon; San Diego, California, Oakland, California; Riverside, California; Sacramento, California; Denver, Colorado; Iowa City, Iowa, Wichita, Kansas; Saint Paul, Minnesota; and the states of Connecticut, Kansas, Missouri, North Carolina, Pennsylvania, Texas, and Washington.²

Perhaps the strongest evidence of racial profiling in policing comes from a 2005 Bureau of Justice (BJS) study. The BJS study showed clear evidence of racial profiling nationally, based on the finding that blacks and Hispanics were more likely to be searched following a stop yet no more likely to be found in possession of contraband. While whites only had their cars searched 3.5% of the time, blacks and Hispanics had their cars searched 10.2% and 11.4% of the time, respectively (Bureau of Justice Statistics, 2005).

Allegedly, Lawrence Greenfeld, head of the Bureau of Justice Statistics, refused to follow orders from the Justice Department to downplay the study's conclusions in a news release (Lichtblau, 2005). As such, he was released from his position. According to the Leadership Conference on Civil Rights (2005), the BJS report confirms that “profiling by federal, state, and local law enforcement agencies is widespread, and that, despite the efforts of some states and local law enforcement agencies to address this problem, federal legislation is necessary.”³

Studies of individual cities, such as Oakland, California, find similar results. For example,

Ridgeway (2006) found that black drivers were twice as likely as white drivers to be searched after being stopped, and only 18% of the searches led to an arrest. Further, the duration of the stop was longer for blacks than whites. A study in Miami found that minorities were not more likely to be stopped but were treated differently after being stopped (Alpert, Dunham, and Smith, 2007).

In spite of such seemingly consistent findings, other studies have found less or no evidence of racial profiling (Skolnick, 2007). For example, the North Carolina Highway Traffic Study found “considerable variation in the racial distribution” of citations and written warnings “across the types of behaviors that were likely to have resulted in the citation or written warning incident (such as speeding or unsafe vehicular movement)” (Smith et al, 2004: 4). The authors acknowledged that “[d]ata on stops, citations, and written warnings that allow for a simple statistical summary for the state as a whole show evidence of racial disparity against African Americans.” For example, African Americans made up only 20% of state drivers but nearly 25% of all those cited for speeding (Smith et al. 2004: 238). Yet, without measures of racial composition of highway drivers or violation rates by race, the researchers were unable to definitively say racial profiling is a problem on the state’s highways.

Further, according to these authors, “objectively measured indicators of violating behaviors in citations” more often involved black drivers, which is suggestive of “the possible importance of variations in driver’s behavior as a primary determinant of whether or not someone is cited” (Smith et al. 2004: 4). That is, driver behavior (including speeding) rather than race could be the determinant of police stops, something that has been confirmed in other studies (Lange, Johnson, and Voas, 2005). The authors conclude that “one can neither rule out the possibility that racial bias explains some of the variation in racial disparity, nor assert that it is

unequivocally present in any geographic area or in the workings of any specific trooper. Put simply, the current level of science is inadequate to the determination of whether disparity can be explained by bias or by one or the other of the rival hypotheses" (Smith et al, 2004: 242).

The authors reason that if a racial bias does operate, it occurs at the local level and is probably at the unconscious "cognitive" level (Smith et al, 2004: 9). Warren et al (2006: 731) suggest that in North Carolina, factors such as race may continue to influence local police behavior. This would be consistent with the claim by some of an "innocent bias" that plagues American policing (Robinson, 2005), which is created in part by an officer's life experiences including interactions with people of color (Peruche and Plant, 2006).

The variation of findings of studies on racial profiling is likely attributable in part due to different locations studied (e.g., New Jersey versus North Carolina), the level of law enforcement studied (e.g., local versus state police), and may also be due to how data are collected, how key variables are operationalized, and whether certain control variables are introduced (Engel, Calnon, and Bernard, 2002; Gold, 2003; Harris, 2003; Parker et al., 2004; Walker, 2001; Warren et al. 2006; West, 2003). For example, many studies do not explicitly consider those "tremendous number of factors other than bias (that) can legitimately influence police decisions to stop drivers" (Fridell, 2004: 3).

At a minimum, studies should control for the *quantity factor* (i.e., some groups of people drive more than other groups of people), the *quality factor* (i.e., some groups of people violate traffic laws more than other groups of people), and the *location factor* (some people drive more in areas where police make more stops than others) due to higher police presence and/or the employment of more aggressive policing techniques. Typically, while some studies of racial profiling attempt to control for the quantity and quality factors, either directly or indirectly, they

tend to ignore the location factor, or spatial elements of law enforcement outcomes as they relate to racial profiling.

One study did take into consideration the “type of the community” based on racial composition (Meehan and Ponder, 2002). Focusing on police officers’ conception of place, rather than on differentiated law enforcement by police agency, the authors proposed that black drivers are more likely to be subject to disproportionate surveillance and traffic stops by the police when they drive in white communities; this is because police officers tend to suspect that a driver might be engaged in criminal activities when the driver’s race does not match the racial composition of a particular area. The authors concluded that “profiling significantly increases as African Americans move farther from stereotypically „black“ communities and into wealthier, whiter areas; a phenomenon we call the *race-and-place* effect.” In other words, “(b)eing an African American driver in a whiter area has more negative consequences than being an African American driver in a blacker area of the same community” (p. 401).

One problem with the study is that it simplified racial profiling as a matter of an individual officer’s behavioral pattern derived from the conception of place, and did not take into account a systemic intervention by organizations in patrol assignments dependent on types of areas. Further, racial difference in police treatments was not investigated in the study. The authors of the study did assume that a “commonsense geography” occurs among police whereby officers know the racial composition of places where drivers are located and that they utilize a “cognitive schema” that identifies suspicious behavior by African Americans, especially in whiter areas. The authors conclude that “racial profiling is inextricably tied not only to race, but to officers’ conceptions of place of what *should* typically occur in an area and *who belongs* as well as *where they belong*” (p. 402).

This finding can be tied to the “racial threat” (Parker, Stults, and Rice, 2005; Stolzenberg, D’Alessio, and Eitle, 2004) or “minority threat” (Holmes, 2000; Stults and Baumer, 2007) hypothesis suggesting that police are assigned in higher numbers to certain areas of a community where minority residence is higher. The war on drugs is one reason there is intensive deployment in minority communities (Robinson and Scherlen, 2007). Given that the police conceive minority communities as places where drug use and trafficking occur in open markets, more aggressive crackdowns in these areas are accepted as an effective utilization of limited police resources. However, it is clear from national studies of drug use such as the National Survey on Drug Use and Health (NSDUH) that rates of drug use for blacks are not significantly higher than for whites. The 2007 NSDUH found past-month drug use rates of 9.5% for blacks versus 8.2% for whites, but the 2001 survey found nearly identical rates for blacks and whites (6.9% versus 6.8%, respectively) (Robinson and Scherlen, 2007).

A recent study of Seattle drug arrests found that nearly two-thirds of arrestees were black even though the only drug for which blacks made up a majority of dealers was crack cocaine; the majority of those involved in dealing methamphetamine, ecstasy, powder cocaine, and heroin were white (Beckett, Nyrop, and Pfingst, 2006). The authors attribute the disparity to three organizational factors: 1) an explicit focus by police on crack offenders; 2) an explicit focus by police on outdoor drug activity; and 3) racially diverse outdoor drug markets received more attention by police than predominantly white outdoor drug markets. The authors concluded that “the geographic concentration of law enforcement resources is a significant cause of racial disparity” (p. 129).

Ecological studies of policing have shown for years that policing efforts vary widely by community characteristics (Sherman, 1986). For example, a study of sixty neighborhoods in

three large US cities showed that assistance offered to citizens and contact with suspicious persons by police were higher in racially heterogeneous neighborhoods (Smith, 1986). Further, suspects encountered in poor areas were three times as likely to be arrested as those encountered in higher income neighborhoods, “regardless of type of crime, race of offender, offender demeanor, and victim preference for criminal arrest” (p. 313). In the study, racial composition of the neighborhood rather than the race of individuals encountered by police seemed to account for use of coercive authority by police.

Some studies do find that, when stopped by police officers, blacks are more likely to be found in possession in larger amounts of some drugs than whites, even when they are no more likely overall to be in possession of drugs (e.g., Lichtenberg, 2006). Another study in New York City found significant evidence of racial disparities for drug offenses such as smoking marijuana in public as part of the department’s quality-of-life, zero-tolerance program (Golub, Johnson, and Dunlap, 2007).

If people of color are more involved in certain crimes, or are expected to be in possession of larger amounts of drugs, it would be logical to assume that a higher frequency of traffic stops for blacks and Hispanics will result from more assignments of patrol in minority residential areas. Similarly, more aggressive law enforcement in minority communities may be the primary reason why black and Hispanic drivers are treated differently by police officers. Racial disparity on the level of individual stops may thus be explained by racial disparities at the level of police beats. That is, minority drivers may be disproportionately stopped and differently treated after stops because they are stopped more often in minority areas where greater numbers of stops are made and where a more intensive policing style is utilized. Focusing on both the micro- and macro- levels potentially allows one to better understand the issue of police profiling.

The current study assumes that the frequency of traffic stops and types of police treatments after stops are dependent upon areas characterized by the deployment density of the police and the proportion of blacks in the population. Given that each area of study has different racial proportions, differentiated police deployment in terms of frequency and intensity will affect the total disparate frequency of stops and police treatments among racial groups. The primary focus in this study is on the extent and the direction that two location-related variables affect the racial difference in traffic stops.

METHOD

DATA

Traffic stop data were collected from January through December 2003 by the Houston Police Department, Texas. The data collection was conducted in compliance with Senate Bill 1074, which mandates every police agency to compile data about race or ethnicity whenever traffic and pedestrian stops are made. The police department utilizes a computer-based data compilation system whereby officers are required to select an appropriate option regarding race and gender of the person stopped, the reason for the stop, the disposition of the stop, the type of search involved, whether contraband was discovered, and the type of charge as a result of the stop.

In this study, 333,760 traffic stops in 121 beats were analyzed. Only included were the traffic stops in which the driver's race/ethnicity was white, black or Hispanic. The baseline for comparing the frequencies of traffic stops among different racial/ethnic groups was the racial/ethnic proportion of population 15 years and above based on the American Community Survey 2003.⁴ Without available data on the actual driving population and the racial/ethnic proportion of drivers, we chose the driving age population as a proxy of the driving population. Despite the potential problem of non-representativeness, this threshold population has been

commonly used in previous racial profiling studies (for review of the baseline issues, see Batton & Kadleck, 2004; Engel, Calnon, & Bernard, 2002). The expected number of traffic stops for each racial/ethnic group was estimated based on the proportion of the driving age population by race/ethnicity.

At the macro-level, we utilized the geographic files in the 2000 U.S. Census data and a beat map file to estimate populations and racial proportions in the police beats. Using a GIS program (ArcGIS 9.0), TIGER/Line files downloaded from the U.S. Census website were overlaid with the beat map in the police department. Then, the U.S. Census demographic data layer was plotted over those maps, aggregating demographic information on the census block level into that of the beat level. Finally, patrol deployment data on the police department were used to estimate the distribution of police force over the beats. The data contain patrol assignments by beats from January through December 2003.

MODELING STRATEGIES

In the macro-level analyses, we attempt to investigate how the spatial characteristics of the policing areas are associated with the various aspects of the racial profiling contention. A simple approach would be computing the OLS regression to predict the dependant variables with the predictors. The OLS method, however, may not be appropriate with a geographic unit of analysis, especially when the value of a variable at one area is conditioned by adjacent areas, which is called “spatial autocorrelation” or “spatial dependence.” If neighboring areas show a similar value because of the geographical proximity, it will lead to underestimated standard errors, resulting in an inflation of values t or F and therefore committing a Type I error (Martin 2002).

First, we conduct an Exploratory Spatial Data Analysis (ESDA) to examine the spatial

autocorrelation of the dependent and independent variables. Moran's I statistic is applied to test the null hypothesis that values on a variable are not geographically related, meaning distributed randomly over the study area. A significant coefficient rejects the null hypothesis, indicating "positive spatial autocorrelation" of traffic stops and adverse stop outcomes (Anselin, 2003). In addition to testing spatial autocorrelation globally, we apply a spatial clustering analysis to identify the areas where traffic stops and adverse stop outcomes are significantly concentrated. And the identified clusters can be compared to the residential distribution by race/ethnicity and the geographic distribution of police resource. Residential segregation by race/ethnicity especially in a metropolitan city has been consistently reported in numerous sociology studies. While some sociologists explain the uneven residential distribution by race/ethnicity as a simple result of a natural market competition (Massey, 1985), others argue that it results from intentional efforts to segregate people of different race/ethnicity (Logan, Alba, & Leung, 1996a; South & Crowler, 1997). No matter what the reason is, each racial/ethnic group tends to form a residential cluster in a different area. Police resource also is more likely to be clustered than evenly dispersed. Police agencies assign more patrol to high crime areas. More police force is demanded from particular areas than others mainly through calls for service.

The similarity or dissimilarity among near locales is determined by the Local Moran LISA statistics at $p < .05$, and displayed by LISA Cluster Maps, which show four different types of spatial autocorrelation (Anselin, 2003). Positive spatial autocorrelation is indicated by high-high locations (i.e., clustering of similar beats with high values) and low-low locations (i.e., clustering of similar beats with low values). Negative spatial autocorrelation is displayed by high-low locations (i.e., beats with high values adjacent with those with low values) and low-high locations (i.e., beats with low values adjacent with those with high values). In the current study,

neighboring beats are determined by “queen contiguity,” whereby any beats sharing either boundaries or vertices are regarded as neighbors (Anselin, 2003).

Assuming that significant spatial autocorrelation is detected, to avoid the aforementioned Type *I* error, the proper model needs to take into account a level of spatial dependence, the degree to which the value of a variable among adjacent areas is correlated. In the previous research, two different models have been applied to deal with the spatial dependence issue: a spatial lag model and a spatial error model. The former assumes that events in one area have an influence on the likelihood of the same events in adjacent areas (Baller et al., 2001). This model corresponds to the spill-over effect or the diffusion process of crime which posit that high crime rates in one area increase crime rates in nearby areas simply due to the geographic adjacency. In the spatial lag model, included is an additional variable into the regression specification. The variable is called “a spatially lagged dependent variable” or “a spatial lag” (Anselin, 2006). A spatial lag amounts to the averaged value of a variable in the neighboring areas. The spatial lag model is written as:

$$y = \rho W y + X\beta + u,$$

where ρ is the spatial autoregressive coefficient, $W y$ is the spatially lagged dependent variable for an $n \times n$ spatial weights matrix W , β is the regression coefficient, and u is the error term (Anselin, 2006).

While the spatial lag model controls for the spatial autocorrelation by entering a lagged dependent variable, the spatial error model incorporates the spatial autocorrelation in the regression error term (Baller et al., 2001). In the spatial error model, the spatial dependence is treated as a result of the influence of unmeasured independent variables. The assumption is that certain variables not included in the model exert influence over the adjacent areas, resulting in

spatially correlated errors (Anselin, 2006). The spatial error function is written as:

$$y = X\beta + \lambda W\epsilon + u,$$

where λ is the spatial autoregressive coefficient for the error lag $W\epsilon$, and W is an $n \times n$ spatial weight matrix (Anselin, 2006).

The current study applies both models based on the assumption that the spatial autocorrelation of traffic stops and adverse stop outcomes may result from the spill-over effect or the influence by unmeasured predictors. First, a large number of traffic stops in one area may increase the likelihood of traffic stops in the neighbors. Given that no area is isolated like an isle but it is surrounded by other areas, police activities in one area will increase the amount of police patrol (or police passing at least) in the adjacent areas, leading to a greater chance of police detection. Second, the spatial dependence of an unmeasured variable such as high drug offense rates may cause the spatial autocorrelation of traffic stops. The previous hot spot studies have found that high crime areas tend to be concentrated spatially. Thus, it is logical to assume that the spatial clustering of crime coincides with the concentration of police activities.

MEASURES

Table 1 describes the variables included in the micro-level analysis. Under the data compilation system in the department, race/ethnicity is divided into five categories: white, black, Hispanic, Asian, and Native American. The current study included only the traffic stops in which the driver's race/ethnicity was white, black or Hispanic.

[Insert Table 1 about here]

For the police stop variables, we followed the classification in the traffic stop data. Stop reasons included non-moving traffic violation (e.g. child restraint violation), moving-traffic violation (e.g. speeding), and investigation. Investigatory stops are justified as long as the facts

and the circumstances sufficiently support that the driver is engaged in a criminal activity. Stops culminate in one of three outcomes. First, the driver is released if no law violation is found or the officer exercises discretion in favor of the driver. Second, the officer can issue a ticket for a law violation – especially traffic laws. Finally, the driver may be arrested if the driver is found to have committed more serious offenses like drug possession. A police officer may conduct a search of the driver, passengers, and/or the vehicle (e.g. trunks and glove compartments) without a search warrant. However, the police officer is required either to obtain consent from the driver or to establish probable cause that the driver has committed or is about to commit a crime (e.g. observing or smelling drugs in the car). In most cases, police searches target contraband such as drugs and guns. The rate of successful searches (i.e. the ratio of contraband findings to searches) is called a “hit rate.” During the final stage of a police stop, the driver is charged with a traffic offense, misdemeanor, or felony depending on the type of offense accused.

[Insert Table 2 about here]

Table 2 shows the variables included in the macro-level analysis. We chose a variety of dependent variables that indicate racial disparity in traffic stops. The percentage of investigatory stops represents the likelihood to be stopped for the purpose of investigation, wherein the officer may exercise greater discretion than in moving or non-moving traffic stops to decide to stop a vehicle. Adverse stop outcomes were measured by the percentages of arrests, searches, felony charges, and contraband detection.

The next group of dependent variables measures the ratio of one stop outcome variable to the other. According to racial profiling claims, minority drivers are the primary target of investigatory police stops, which are often made without sufficient legal grounds. If this claim is accurate, it is predicted that many minority drivers stopped for investigation are more likely to

ultimately be released because of a lack of evidence to charge them. This variable is measured by dividing the number of releases by the number of investigatory stops. Next, the “pretextual stop” contention posits that police utilize minor traffic violations as opportunities to investigate other criminal offenses (e.g. drug offenses). And the pretextual stop tactic is used disproportionately and adversely against minority drivers. Following the argument, a police officer may be more likely to conduct a search of the driver (if the driver is a minority) after moving or non-moving traffic stops. The pretextual stop variables include the ratio of searches to non-moving stops and the ratio of searches to moving stops. Finally, if more police searches are conducted of minority drivers – not because of legal factors, but because of extralegal factors (i.e. race and ethnicity) – the “hit rate” must be lower for minority drivers. The hit rate is measured by dividing the number of contraband findings by the number of searches.

The independent variables are characteristics of police beats, consisting of the percentage of black residents, the percentage of Hispanic residents, police resource commitment, and the total population. Police resource commitment, a measure of the concentration level of patrol assignments, is calculated by dividing the number of police-initiated deployments in each beat by the total number of shifts for one year. Given three shifts in a day, the annual total number of shifts is the total number of days (365) times three, which equals 1,095. The outcome figure represents the average number of patrol units deployed per shift during the year of 2003 in a particular beat.

In the macro-level analysis, 15 beats out of the total 121 are excluded for several reasons. Eleven beats are disqualified because no information is available on the amount of deployment. Three beats with population below 1,000 are excluded because the rates of stops in these beats are extraordinarily high, which is called a “small area problem.” Estimates based on a small

population often constitute outliers, not because of characteristics on issue, but because of the small population at risk. Another outlier beat is disqualified because of an extremely low number of stops (7) compared to the population size (13,556). After the clean-up, the total 106 beats are left for the analysis.

FINDINGS

RACIAL DISPARITY IN TRAFFIC STOPS AT THE MICRO-LEVEL OF ANALYSIS

In our study, black drivers were stopped more often than any other racial/ethnic groups. More than half of the stops were investigatory stops, followed by moving traffic offense stops. The majority of drivers were released and not subject to a search. When officers conducted warrantless searches, they justified them based on probable cause rather than consent from the driver. Only a small number of traffic stops (1.5%) ended up finding contraband. About a quarter of drivers were charged with traffic offenses and felony charges accounted for only 3% of all stops (see Table 1).

[Insert Table 3 about here]

The first analysis compares racial disparity in the number of traffic stops among three different stop reasons. As shown in Table 3, the expected numbers of stops in the table were estimated by population 15 and above of each racial/ethnic group within the police department's jurisdiction. Blacks were the only racial/ethnic group that was disproportionately stopped regardless of stop reasons. While black drivers were stopped 13.9% more often for non-moving traffic reasons and 7.6% more often for moving-traffic reasons than expected, both whites and Hispanics were less stopped than expected. Investigatory stops followed a similar distribution, with more stops for blacks and less stops for the other groups. The greatest overrepresentation of blacks was found in investigatory stops with 17.3% more stops than expected. Despite the

statistically significant chi-square values for all the comparisons, the differences between observed and expected investigatory stops were much greater than those for the other stop reasons. These results show that racial discrepancy is greater in investigatory stops for which police officers rely on more discretionary determinants such as a probable cause, than in moving or non-moving traffic stops, which require manifest traffic violation. In this sense, these findings are consistent with the racial profiling claim that police officers exercise greater discretion unfavorably for black drivers.

[Insert Table 4 about here]

Table 4 shows racial disparity in various outcomes after traffic stops. Hispanics and blacks were more likely than whites to be arrested after stops, whereas white drivers were more likely to be released. Police conducted searches more frequently of black and Hispanic drivers. While about 15% of black or Hispanic drivers were searched based on probable cause, only 8.5% of white drivers were searched. In spite of the similar pattern, the racial difference in consent searches was not as severe as in probable cause searches: 2.1%, 3.9%, and 3.0% for whites, blacks, and Hispanics, respectively. The findings show that when officers stopped black or Hispanic drivers, they were more likely not only to conduct a search, but also to resort to probable cause rather than the driver's consent. The greater reliance upon probable cause may be related with the finding that more black or Hispanic drivers were stopped for an investigation purpose. When a police officer stops a vehicle to investigate a criminal offense, he/she is required to establish probable cause that the driver has engaged in a criminal activity based on the totality of circumstances. Once the police officer stops the vehicle, probable cause for a vehicle search can be developed through an observation (e.g., the driver is trembling and appears to be extremely nervous) or plain view (e.g., a bag of marijuana on the floor). Given the

existence of a suspicion prior to a stop, one or more suspicious elements can easily advance the situation to a searchable one. Thus, police officers may not need to obtain consent from the driver.

The odds to discover contraband were highest when blacks were stopped; 2.2% of traffic stops for black drivers resulted in contraband whereas about 1% of stops led to contraband for whites or Hispanics. This discrepancy may be a result of the greater amount of searches conducted against black drivers. This reasoning, however, does not appear to be valid if we take into account Hispanic drivers. Although Hispanics also were subject to a disproportionate level of police searches, contraband was not found in their searches as much as in searches of black drivers. Thus, it is likely that black drivers actually possessed contraband more often than their racial/ethnic counterparts. We recognize, however, that this simple conclusion may be myopic without taking into account the organizational factors in police agencies. Law enforcement activities in black communities place more emphasis on narcotic crackdowns because of higher perceived rates of drug offenses. The police initiative to enforce drug offenses in drug hot spots, which are more likely to be located in black communities, may lead to a higher probability of contraband for black drivers.

Finally, while whites were more likely to be released without being charged, the risk of being charged with a felony was highest for blacks. Hispanics were overrepresented in the categories of traffic charges and misdemeanor charges. The greater felony charges for blacks may be a subsequent outcome of the higher likelihood to find contraband.

SPATIAL ASPECTS OF TRAFFIC STOPS AT THE MACRO-LEVEL OF ANALYSIS

To test spatial autocorrelation of the variables, we conducted the ESDA using GeoDa 0.9.5i, a spatial statistical software package developed by Luc Anselin (2003). First, an estimation of a

global spatial autocorrelation was performed to test the strength and significance of spatial autocorrelation for the variables. The test results are displayed in Table 5, showing that the null hypothesis of spatial randomness is rejected for all the independent and dependent variables. Although the coefficients of Moran's I statistics are positive and statistically significant for all the variables, they are greater than others for the percent of blacks, Hispanics, investigatory stops, arrests, and felony charges.

[Insert Table 5 about here]

Next, a spatial clustering analysis was conducted to identify the areas with significant spatial autocorrelation. Figure 1 shows spatial clustering of the independent variables: the percentage of blacks, the percentage of Hispanics, and resource commitment. The first two maps reveal apparent racial segregation in the jurisdiction of the police department. Black communities are concentrated in the north and the south of the downtown area of the city, and non-black communities are spread out westward. Hispanic communities also are clustered in the north and the south, but are not spatially overlapped with the black communities. The resource commitment map appears to follow the spatial pattern of the two minority population maps. More patrol is deployed in black or Hispanic areas, generating hot spots of police force.

[Insert Figure 1 about here]

Figure 2 shows LISA cluster maps of the dependent variables: the number of total traffic stops, the percentage of investigatory stops, arrests, consent searches, probable cause searches, contraband findings, and felony charges. In general, unfavorable stop outcomes are significantly clustered in black and/or Hispanic residential areas and hot spots of police force. Significant high-high LISA clusters of arrests, probable cause searches, consent searches, contraband detections, and felony charges are located in areas where blacks and Hispanics are concentrated

and more patrol is deployed

However, the LISA clusters for the number of traffic stops and the rate of investigatory stops do not match the spatial concentrations of the independent variables. Most of the high-high clusters are located outside the black or Hispanic residential areas or the police resource concentration areas. Interestingly, drivers are more likely to be stopped for investigation in areas where patrol is less concentrated. This finding is opposite to our expectation that more patrol will be assigned to the areas which are more vulnerable to crime, and police officers will make stops to investigate criminal activities rather than enforce traffic laws.

[Insert Figure 2 about here]

Given the significant spatial autocorrelation detected, we estimated spatial regression models instead of an OLS model to take into account the effects of spatial dependence. Table 5 shows the results of spatial lag models. In areas with a greater black population, drivers are more frequently stopped, subjected to consent searches, found in possession of contraband, and charged with a felony. However, the percentages of investigatory stops, arrests, and probable cause searches are not significantly related with the percentage of blacks. The ratio of releases to investigatory stops is not significantly higher in black neighborhoods, which is not compatible with the racial profiling claim that more unnecessary and groundless stops are conducted in black communities targeting black drivers. Drivers in black communities are more likely to be searched after both non-moving and moving traffic stops. The magnitude of the effect is relatively stronger when it comes to the likelihood of search after a moving traffic stop. According to these results, “pretextual stops,” in which police take advantage of traffic violations to investigate more serious offenses, appears to be more prevalent in black communities. This is suggestive of racial profiling. Yet, the hit rate to detect contraband over searches is found higher

in black communities. This finding is inconsistent with the racial profiling contention that unnecessary and groundless searches, which tend to end up with finding no contraband, are more prevalent in black communities. That is, the higher hit rate in black communities may indicate that more drivers are in possession of contraband in those areas, warranting greater police vigilance, which may justify more intensive law enforcement.

[Insert Table 5 about here]

The percentage of Hispanic residents is positively related only with the percentages of arrests and consent searches. Thus, drivers are more likely to be arrested and be searched by consent in Hispanic communities. Resource commitment is positively related with the number of stops, the percentages of arrests, probable cause searches, contraband detections, and felony charges. These results indicate that more intensive law enforcement, through more frequent stops and more adverse outcomes, is conducted in the areas with greater police force. Furthermore, drivers who are stopped for investigation in these areas are less likely to be released. In other words, drivers are more likely to be either ticketed or arrested after investigatory stops. This finding may indicate that police officers rely on legal factors in their decision to make an investigatory stop, which reduces the risk of futile stops. An alternative interpretation is that the finding may simply show more punitive attitude among police officers working in these areas. The hit rate to detect contraband after a search is higher in the areas where greater police resource is committed. This finding may indicate that either drivers in these areas are more likely to possess contraband or police searches successfully target rightful suspects.

Table 5 also shows positive and significant effects of the spatial lags of investigatory stops, arrests, probable-cause searches, contraband detection, felony charges, the ratio of release over investigatory stops, the ratio of search for moving traffic stops and the hit rate. However, the

findings do not support the diffusion process for the number of traffic stops. That is, the influence of a large number of traffics stops in one area upon the neighbors cannot be explained by an increase in police detection in the neighboring areas due to the simple geographic proximity.

[Insert Table 6 about here]

The results of the spatial error models are shown in Table 6. The effects of black population and Hispanic population upon traffic stops and stop outcomes are similar as shown by the spatial lag models. However, the effect of resource commitment is significant only for the number of stops and the percent of arrest. Unlike the spatial lag model, resource commitment in the spatial error model is not significantly associated with probable-cause search, contraband detection, felony charge, the ratio release over investigatory stop, and the hit rate of contraband. Such differences between the two models may be due to the different magnitude in the effect of spatial lags and spatial errors upon those variables; the effects of spatial errors are substantially stronger than spatial lags. Hence, the variances of the independent variables in the spatial error models are mostly accounted for by the spatial errors, leaving no room for resource commitment to explain.

These findings also indicate that resource commitment may be significantly related to the spatial errors, or unmeasured variables. The most plausible unmeasured variables include drug offense rates. Following the policy suggestions by problem-oriented policing and hot spot policing, police resources, instead of being spread evenly over the police jurisdiction, are more committed to a few drug “hot spots,” which coincide with areas where the police are more likely to conduct probable cause searches, retrieve contraband, charge an offender with a felony, make an investigatory stop, and generate a higher hit rate for contraband detection. Thus, the introduction of the spatial errors into the regression models substantially diminished or negated

the effect of resource commitment upon the dependent variables.

The results also show that the spatial error is significantly related with the number of stops, indicating that the spatial autocorrelation of the number of traffic stops results from unmeasured variables such as drug offense rates, rather than a diffusion process. The spatial error models provide a better fit than the spatial lag models for most of the dependent variables. Improvement of a model fit is most noticeable for investigatory stop, felony charge, the ratio of release over investigatory stop, and the hit rate for contraband detection.

DISCUSSION

Prior to discussing the findings, we should acknowledge that some methodological limitations warrant cautious interpretation of the results. First, this study cannot overcome the Modifiable Areal Unit Problem (MAUP) like many other studies using geographic units. With a police beat as the unit of analysis, the visual representations of the hot spots on the LISA Cluster maps are affected by the size, shape and orientation of the geographic areas (Chainey & Ratcliffe, 2005). Furthermore, the estimations of the variables (e.g. the number of traffic stops) are restrained by the geographic boundary, which is created for the administrative or governmental purpose in an arbitrary way. Second, reliability can be an issue in measuring Hispanics because it is relatively hard to distinguish Hispanic ethnicity by one's appearance. Thus, chances are that some people who were classified as Hispanics in the traffic stop data might be counted as members of the other racial groups in the U.S. Census. If this is the case, the number of Hispanic drivers may be overestimated in the traffic stop data. Finally, the current study relies only upon the amount of police resources as a measure of police resource commitment. However, law enforcement initiatives, which may be relevant to discriminatory policing practices, include not only the quantity, but also the quality or the kinds of police resources. For example, a special

crime control unit, such as a narcotic enforcement task force, is disproportionately assigned to disadvantaged minority communities. This issue of unmeasured variables was handled in an indirect way through the introduction of the spatial errors into the regression models.

Despite the aforementioned limitations, the findings of the current study reveal noteworthy aspects in the spatial distributions of policing practices and their associations with the community context. The primary purpose of this study was to examine the spatial association between the characteristics of patrol areas and the patterns of traffic stops. Specifically, this study assumed that more traffic stops are conducted and more adverse outcomes are generated in the areas where minority people are concentrated and more police resource is committed. This assumption is supported by the empirical findings that these areas often spatially coincide with high crime neighborhoods in which more intensive law enforcement is performed. Although this study could not provide clear evidence that racial disparity in individual traffic stops is contingent upon the disparity in traffic stops at the community level, the findings in this study suggest that these two facts may be associated. Simply put, minority drivers may be stopped, searched, arrested, and charged with a felony because they are more likely to drive in high crime areas where they reside and more vigorous law enforcement is a common practice.

The micro-level analysis of individual stops confirmed the existence of a racial disparity in the number of traffic stops and subsequent outcomes. Blacks were overrepresented and the other racial/ethnic groups were underrepresented in traffic stops. Furthermore, blacks were found to be disproportionately involved with traffic stops in situations where officer discretion played a greater role in decisions to stop. The racial disparity was greater in investigatory and non-moving traffic stops than in moving traffic stops. In terms of stop outcomes, black and Hispanic drivers, once stopped, were more likely to be arrested and searched than white counterparts. More blacks

than any other racial/ethnic group were found to possess contraband and were eventually charged with felonies.

The spatial analysis at the macro-level found that the areas with more frequent traffic stops and more adverse stop outcomes were spatially clustered rather than dispersed, and the majority of the clusters spatially coincided with minority residential areas and/or police resource concentration areas. The multiple regression analysis, affirming the exploratory findings of the cluster map analysis, found statistically significant associations between the characteristics of patrol areas and the traffic stop patterns; a greater number of stops were made and more adverse stop outcomes were followed as more minorities live and/or more patrol is assigned in the community.

Not only are traffic stops concentrated on particular racial or ethnic groups at the micro level, but also they vary by place. That is, there are certain places (e.g. beats or streets) that traffic stops are more likely to occur and drivers are more likely to be searched or arrested. Greater police force and more intensive law enforcement are applied to “hot spots” where more crimes occur. The demand for police service also tends to cluster in certain areas, heightening the likelihood of traffic stops. While selective law enforcement based on race/ethnicity is often disapproved as racially discriminatory, differentiated policing by place is supported in most police agencies as an effective crime control strategy. Insofar as the different treatment by place is grounded upon legal factors (e.g. crime rates), greater police force along with more intensive enforcement for particular areas does not bring up a discrimination issue.

A great deal of research during the last decade provided police departments with a valid justification for a geographically differentiated policing strategy. Since the groundbreaking work by Sherman and his associates (1989), a number of studies have searched for hot spots of various

types of crime in different areas. In the study conducted in Minneapolis, Sherman and his associates identified hot spots that produced over 50% of calls to police but accounted for only 3% of all addresses and intersections.

Hot spots have been identified for different types of crimes, including gang violence (Block and Block, 1993), drug offenses (Block and Block, 1995), burglary (Hirschfield et al., 1995), car theft (Fleming, 1994), gun violence (Sherman and Rogan 1995), among others. Thus, if the occurrence of crime is geographically concentrated and the hot spots are predictable, police agencies may prevent crimes or at least reduce crime rates by concentrating police force in these locations. The hot spot studies provide an empirical basis for implementing “problem-oriented policing.” Unlike traditional policing that attempts to deal with general crime or social disorder, the problem-oriented approach targets more specific problems or specific types of crime (Goldstein, 1977). Under the problem-oriented approach, the police are expected to analyze specific problems in a neighborhood, and then respond to the problems with most appropriate strategies.

Many evaluation studies reveal that problem-solving strategies based on hot spot analysis are effective in reducing crime rates and disorder problems. For example, Sherman and Weisburd (1995), in the experimental study conducted in Minneapolis, found a substantial decrease in crime rates and disorder in hot spots when they doubled the amount of patrol. Similar crime reductions were also reported for different types of crimes, including residential burglary (Eck and Spelman, 1987), prostitution (Matthews, 1997), drug selling (Hope, 1994), as well as others.

Numerous studies also found that high crime rates – especially street crimes – are associated with neighborhoods with high rates of poverty and economic deprivation and a high proportion of non-whites (Robinson, 2004). Macro-level studies analyzed this as a structural

problem in poor, non-white communities, which failed to develop an effective social control mechanism. As crime is spatially concentrated in particular areas, residences are also spatially segregated by different racial groups. The uneven distribution of residences may be determined either by the principle of market rules based on economic affordability (Massey, 1985), or by whites' willingness to maintain racial homogeneity in their neighborhoods (Logan et al., 1996a, 1996b; Massey and Denton, 1988; South and Crowder, 1997).

No matter what the reason is, there exist racially/ethnically minority communities where social problems are concentrated. And these communities often constitute hot spots of crime and disorder, which draw greater attention from police agencies, and consequently invite more intensive law enforcement activities. The problem-oriented policing strategy, accompanied by scientific analyses (e.g. a hot spot analysis and crime mapping with the Geographic Information System), is widely understood as a legitimate effort by police administrators to maneuver police resource more efficiently and effectively. This study found that more police resource was committed to minority communities, and in these communities, more traffic stops and more adverse outcomes occurred. If the disparity in traffic stops by geographic areas could explain a substantial amount of racial disparity at the individual level, the racial profiling argument may be seriously weakened because the police practice that is seemingly race-based (i.e. more minority drivers stopped and arrested) may be a mere consequence of legitimate policing strategies at the department level. However, it will be premature to conclude as such because of the following issues.

This study showed a likelihood of such an interaction between racial disparity at the macro level and at the micro level. However, the findings in this study must be regarded as suggestive rather than conclusive. Despite the significant effects of beat characteristics on the

number of traffic stops and the types of subsequent outcomes, we don't know yet how much of the racial difference on the individual level can be accounted for by the beat characteristics.

Future research is recommended to conduct a multi-level analysis, which includes both macro-level and micro-level factors in the model to examine the role of a driver's race/ethnicity in a traffic stop situation, controlling for relevant factors at the macro level

Furthermore, it is still questionable if the area-specific policing strategies at the department level could neutralize completely the racial profiling claim. When police officers exercise discretion in traffic stops, decision-making is often influenced by subjective perception or knowledge of the patrol area, which is developed through previous experiences or information from fellow officers. Thus, police officers' reactions to similar situations may vary depending on the characteristics of the community. For example, police officers may overreact simply because of their exaggerated perceived risk working in a certain community. If this is the case, the community may experience undue policing, not because of legitimate crime control efforts at the agency level, but because of abuse of discretion at the individual level.

The findings of the current study suggest important policy implications for police agencies. Granted that racial disparity in traffic stops at the individual level is substantially attributed to the disproportionate commitment of police resources at the community level, police agencies still need to consider if such policing strategies, often named problem-oriented policing or hot spot policing, resonate well with the ideal of democratic policing, the imperative for the American police. Democratic policing is often understood as the antonym of inequality, seeking an equal distribution of police service or police control over the public. Thus, unequal amount or different types of police recourses that are devoted to different communities may appear undemocratic. People living in disadvantaged minority communities may perceive that policing

unduly targets their communities, if not minority individuals. Responding to such a complaint, the police may justify that their policing strategies are race-neutral and legitimate, singling out crime hot spots through sophisticated analyses of crime data. This argument could be challenged for two reasons.

First, the validity of official crime data, upon which most police agencies rely to develop policing strategies, has long been questioned. It has been argued that official crime data may be a measure of “official reactions to crime” rather than an actual measure of crime (Warner and Pierce, 1993:494). In this sense, a high concentration of crime in particular areas may simply represent a strong willingness for social control by the police. Thus, crime control policies based upon such data may be criticized as tautological in nature.

Second, it is also questionable if police agencies are entitled to impose policing practices that the community does not want. Another important ethos of democratic policing, especially under participatory or deliberative democracy, is community control of the police through community empowerment and community participation (Sklansky, 2008). A community’s status should not be limited as the consumer of police service, but the community, as a co-producer of police service, must play a key role in the producing process. A community should be entitled to determine the amount and the types of police service. In this sense, unequal treatments by the police, notwithstanding the seemingly race-neutral nature, may be perceived as anti-democratic insofar as the community does not grant them.

One may ask these questions. What if the community wants unequal distribution of police resources to control crime? Should the police simply comply with the demand from the community? What about the other communities that will be under-policed because of the unequal distribution of police resources? As the current study shows, disparities in policing practices at

the community level lead to racial disparities at the individual level. More effective police practices at the community level (e.g. a higher hit rate to detect contraband) may be juxtaposed with a greater likelihood of becoming subject to more frequent and more intensive police practices at the individual level (e.g. more stops and more searches). Thus, it is important that members of a community be informed and fully aware of the potential impact of “over-policing” on individuals. In developing policing strategies, police agencies must take into account the community’s needs and demands as well as crime data. Police agencies also should strive for community support before implementing policing strategies that may arouse a sentiment among the community members that they (their community) are treated in an unequal way.

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TABLE 1. Description of Variables in Micro-level Analysis

| <i>Variables</i> | <i>N</i> | <i>%</i> |
|-----------------------------|----------|----------|
| <i>Independent Variable</i> | | |
| Race | | |
| White | 91720 | 27.5 |
| Black | 131395 | 39.4 |
| Hispanic | 110645 | 33.2 |
| <i>Dependent Variable</i> | | |
| Stop Reasons | | |
| Non-Moving Traffic | 40171 | 12.0 |
| Moving Traffic | 110854 | 33.2 |
| Investigation | 182735 | 54.8 |
| Disposition | | |
| Released | 187255 | 56.1 |
| Ticketed | 86059 | 25.8 |
| Arrested | 60446 | 18.1 |
| Search | | |
| No Search | 279048 | 83.6 |
| Consent Search | 10362 | 3.1 |
| Probable Cause Search | 44350 | 13.3 |
| Contraband | | |
| Yes | 4960 | 1.5 |
| No | 328800 | 98.5 |
| Charge | | |
| No Charges | 187255 | 56.1 |
| Traffic | 88151 | 26.4 |
| Misdemeanor | 48120 | 14.4 |
| Felony | 10234 | 3.1 |
| Total | 333760 | 100 |

TABLE 2. Description of Variables in Macro-level Analysis

| <i>Variables</i> | <i>N</i> | <i>MIN</i> | <i>MAX</i> | <i>Mean</i> | <i>S.D.</i> |
|--|----------|------------|------------|-------------|-------------|
| <i>Dependent variables</i> | | | | | |
| Number of stops | 106 | 113 | 8682 | 3159.47 | 1650.82 |
| % Investigatory stops | 106 | 15.33 | 84.72 | 54.23 | 16.69 |
| % Arrests | 106 | 3.25 | 32.80 | 17.61 | 7.24 |
| % Consent searches | 106 | .42 | 10.26 | 2.90 | 1.96 |
| % Probable cause searches | 106 | 2.21 | 26.85 | 12.82 | 6.28 |
| % Felonies | 106 | .00 | 10.47 | 2.95 | 2.03 |
| %Contraband | 106 | .00 | 7.10 | 1.37 | 1.18 |
| Ratio of releases to investigatory stops | 106 | 38.30 | 90.10 | 64.76 | 11.34 |
| Ratio of searches to non-moving stops | 106 | .00 | 13.81 | 2.22 | 2.31 |
| Ratio of searches to moving stops | 106 | .00 | 13.82 | 1.66 | 2.21 |
| Ratio of contraband findings to searches | 106 | .00 | 37.55 | 8.13 | 4.75 |
| <i>Independent variables</i> | | | | | |
| % Black population | 106 | .94 | 91.71 | 25.75 | 26.58 |
| % Hispanic population | 106 | 4.94 | 92.21 | 35.49 | 23.90 |
| Resource Commitment | 106 | .00 | 4.49 | 1.13 | .79 |
| Population | 106 | 1205 | 57992 | 22172.31 | 11937.19 |

TABLE 3. Racial Differences in the Observed and Expected Number of Stops by Reasons for Stops.

| <i>Stop Reasons</i> | | <i>Observed</i> | <i>Expected</i> | <i>Residual</i> |
|---------------------|----------|------------------|--------------------|----------------------|
| Non-moving traffic | White | 23.1% (9280) | 34.8% (13979.5) | -11.7% (-4699.5) |
| | Black | 39.6% (15891) | 25.7% (10340.0) | 13.9% (5551.0) |
| | Hispanic | 37.3% (15000) | 39.5% (15851.5) | -2.2% (-851.5) |
| | Total | 40171 | | |
| | χ^2 | | | 4605.59** |
| Moving traffic | White | 33.6% (37275) | 34.8% (38577.2) | -1.2% (-1302.2) |
| | Black | 33.3% (36878) | 25.7% (28533.8) | 7.6% (8344.2) |
| | Hispanic | 33.1% (36701) | 39.5% (43743.0) | -6.4% (-7042.0) |
| | Total | 110854 | | |
| | χ^2 | | | 3617.7** |
| Investigation | White | 24.7% (45165) | 34.8% (63591.8) | -10.1% (-18426.8) |
| | Black | 43.0% (78626) | 25.7% (47036.0) | 17.3% (31590.0) |
| | Hispanic | 32.3% (58944) | 39.5% (72107.2) | -7.2% (-13163.2) |
| | Total | 182735 | | |
| | χ^2 | | | 28958.7** |

* $p < .05$ (two-tailed); ** $p < .01$ (two-tailed)

TABLE 4. Racial Differences in Stop Outcomes.

| <i>Stop Outcomes</i> | <i>White</i> | <i>Black</i> | <i>Hispanic</i> |
|-----------------------|------------------|-------------------|-------------------|
| Disposition | | | |
| Released | 61.1% (56023) | 58.3% (76663) | 49.3% (54569) |
| Ticketed | 25.8% (23677) | 21.9% (28790) | 30.4% (33590) |
| Arrested | 13.1% (12020) | 19.7% (25941) | 20.3% (22484) |
| | χ^2 | | 4854.2** |
| Search | | | |
| No Search | 89.4% (82029) | 80.7% (106078) | 82.2% (90939) |
| Consent Search | 2.1% (1917) | 3.9% (5177) | 3.0% (3268) |
| Probable Cause Search | 8.5% (7774) | 15.3% (20139) | 14.9% (16436) |
| | χ^2 | | 3350.7** |
| Contraband | | | |
| No | 99.0% (90837) | 97.8% (128541) | 98.9% (109419) |
| Yes | 1.0% (883) | 2.2% (2853) | 1.1% (1224) |
| | χ^2 | | 702.1** |
| Charge | | | |
| No Charges | 61.1% (56023) | 58.3% (76663) | 49.3% (54569) |
| Traffic | 25.5% (23365) | 22.6% (29659) | 31.7% (35126) |
| Misdemeanor | 11.6% (10678) | 14.5% (19000) | 16.7% (18440) |
| Felony | 1.8% (1654) | 4.6% (6072) | 2.3% (2508) |
| | χ^2 | | 6009.3** |

* $p < .05$ (two-tailed); ** $p < .01$ (two-tailed)

TABLE 5. Spatial Autocorrelation of the Macro-Level Variables

| Variables | Moran's I |
|--|-----------|
| <i>Independent variables</i> | |
| % Black population | .52** |
| % Hispanic population | .48** |
| Resource Commitment | .30** |
| Population | .30** |
| <i>Independent variables</i> | |
| Number of stops | .17** |
| % Investigatory stops | .49** |
| % Arrests | .45** |
| % Consent searches | .18** |
| % Probable cause searches | .39** |
| %Contraband | .41** |
| % Felonies | .47** |
| Ratio of releases to investigatory stops | .32** |
| Ratio of searches to non-moving stops | .13* |
| Ratio of searches to moving stops | .17* |
| Ratio of contraband findings to searches | .30** |

* $p < .05$ (two-tailed); ** $p < .01$ (two-tailed)

TABLE 5. Spatial Lag Models for Traffic Stops

| Independent Variables | <i>STOP #</i> | <i>INVST</i> | <i>ARRST</i> | <i>CONST</i> | <i>PROB</i> | <i>CONTR</i> | <i>FELON</i> | <i>RELS /INVST</i> | <i>SRCH /N_MOV</i> | <i>SRCH /MOV</i> | <i>CONTR /SRCH</i> |
|-----------------------|---------------|--------------|--------------|--------------|-------------|--------------|--------------|--------------------|--------------------|------------------|--------------------|
| % Blacks | 2.21* | .01 | .00 | .15** | .01 | .01** | .01** | .01 | .01* | .02*** | .01* |
| | [4.93] | [1.74] | [.46] | [3.07] | [1.63] | [2.83] | [2.64] | [1.23] | [2.08] | [3.56] | [2.55] |
| | (1.00) | (.01) | (.00) | (.05) | (.01) | (.00) | (.00) | (.01) | (.00) | (.00) | (.00) |
| % Hispanics | 7.77 | .00 | .05 | .68* | .05 | .00 | .02 | -.09 | -.02 | .05 | -.02 |
| | [1.31] | [.01] | [1.96] | [2.32] | [1.49] | [.20] | [1.01] | [-1.78] | [-.68] | [1.92] | [-.50] |
| | (5.92) | (.05) | (.03) | (.29) | (.04) | (.02) | (.02) | (.05) | (.03) | (.03) | (.03) |
| Resource commitment | 13.85*** | -.01 | .04** | .26 | .06** | .02** | .03** | -.06* | -.01 | .02 | .04* |
| | [4.00] | [-.28] | [2.82] | [1.56] | [2.66] | [2.60] | [2.79] | [-2.16] | [-.67] | [1.19] | [2.08] |
| | (3.46) | (.03) | (.01) | (.17) | (.02) | (.01) | (.01) | (.03) | (.02) | (.02) | (.02) |
| Population | .09*** | .00* | .00** | .00 | .00 | .00 | .00 | -.00* | .00 | .00 | .00 |
| | [3.30] | [2.37] | [2.80] | [1.46] | [1.42] | [1.68] | [1.19] | [-2.37] | [1.81] | [.79] | [.94] |
| | (.03) | (.03) | (.00) | (.00) | (.00) | (.00) | (.00) | (.00) | (.00) | (.00) | (.00) |
| Spatial lag | -.12 | .40*** | .59*** | .08 | .39*** | .56*** | .60*** | .28*** | .12 | .22* | .33*** |
| | [-1.30] | [5.57] | [7.78] | [1.00] | [4.65] | [7.02] | [8.36] | [3.68] | [.97] | [2.00] | [3.55] |
| | (.10) | (.07) | (.07) | (.08) | (.08) | (.08) | (.07) | (.08) | (.12) | (.11) | (.09) |
| Constant | 34.21*** | 0.39*** | -.04 | -4.06*** | 0.11** | 0.02 | 0.02 | 0.67*** | 0.12*** | 0.06* | 0.16*** |
| | (6.04) | (.07) | (.02) | (.41) | (.04) | (.02) | (.02) | (.07) | (.04) | (.03) | (.04) |
| R ² | 0.35 | 0.35 | 0.52 | 0.23 | 0.39 | 0.50 | 0.55 | 0.29 | 0.09 | 0.27 | 0.27 |

Note: Standardized regression coefficients and standard errors are reported in brackets and parentheses respectively; STOP# = number of stops, INVST = % of investigatory stops, ARRST = % of arrests, CONST = % of consent searches, PROB = % of probable cause searches, FELON = % of felony charges, RELS/INVST = ratio of releases to investigatory stops, SRCH/N_MOV = ratio of searches to non-moving traffic stops, SRCH/MOV = ratio of searches to moving traffic stops, CONTR/SRCH = ratio of contraband findings to searches.; STOP#, INVST, PROB, CONTR, FELON, SRCH/N_MOV, SRCH/MOV, CONTR/SRCH, % Hispanics, resource commitment, and population are square-rooted; CONST and % blacks are natural-logged.

* *p* < .05 (two-tailed); ** *p* < .01 (two-tailed); *** *p* < .001 (two-tailed)

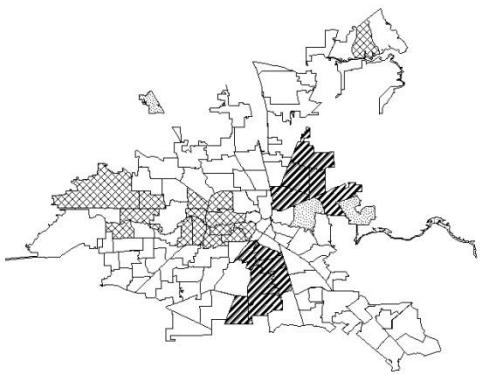
TABLE 6. Spatial Error Models for Traffic Stops

| Independent Variables | <i>STOP #</i> | <i>INVST</i> | <i>ARRST</i> | <i>CONST</i> | <i>PROB</i> | <i>CONTR</i> | <i>FELON</i> | <i>RELS /INVST</i> | <i>SRCH /N_MOV</i> | <i>SRCH /MOV</i> | <i>CONTR /SRCH</i> |
|-----------------------|---------------|--------------|--------------|--------------|-------------|--------------|--------------|--------------------|--------------------|------------------|--------------------|
| % Blacks | 1.95* | .01 | -.00 | .15** | .01 | .01* | .01* | .01 | .01* | .02*** | .02** |
| | [1.61] | [.78] | [-.43] | [2.70] | [.88] | [2.47] | [2.23] | [.76] | [2.09] | [3.70] | [2.89] |
| | (1.21) | (.01) | (.01) | (.05) | (.01) | (.00) | (.00) | (.01) | (.01) | (.00) | (.01) |
| % Hispanics | 5.08 | -.05 | .06 | .72* | .04 | .02 | .04 | -.10 | -.02 | .07* | .03 |
| | [.74] | [-.74] | [1.71] | [2.26] | [.99] | [.87] | [1.56] | [-1.68] | [-.64] | [2.20] | [.70] |
| | (6.83) | (.06) | (.03) | (.32) | (.05) | (.02) | (.02) | (.06) | (.04) | (.03) | (.04) |
| Resource commitment | 14.90*** | -.02 | .05** | .25 | .03 | .01 | .02 | -.06 | -.01 | .02 | .01 |
| | [3.76] | [-.52] | [2.62] | [1.34] | [1.33] | [.97] | [1.61] | [-1.92] | [-.74] | [.97] | [.61] |
| | (3.96) | (.04) | (.02) | (.19) | (.03) | (.01) | (.01) | (.03) | (.02) | (.02) | (.02) |
| Population | .09** | .00 | .00* | .00 | .00 | .00** | .00 | -.00* | .00 | .00 | .00* |
| | [2.85] | [1.73] | [2.47] | [.95] | [1.80] | [2.59] | [2.43] | [-2.05] | [1.89] | [.67] | [2.07] |
| | (.03) | (.00) | (.00) | (.00) | (.00) | (.00) | (.00) | (.00) | (.00) | (.00) | (.00) |
| Spatial error | .39*** | .67*** | .73*** | .24 | .56*** | .70*** | .81*** | .55*** | .09 | .23 | .56*** |
| | [3.45] | [8.72] | [11.09] | [1.94] | [6.11] | [9.66] | [15.68] | [5.79] | [.71] | [1.85] | [6.14] |
| | (.11) | (.08) | (.07) | (.12) | (.09) | (.07) | (.05) | (.09) | (.13) | (.12) | (.09) |
| Constant | 28.83*** | 0.70*** | -.02 | -4.30*** | 0.24*** | 0.06 | 0.08 | 0.86*** | 0.14*** | 0.08** | 0.23*** |
| | (5.76) | (.05) | (.03) | (.28) | (.04) | (.02) | (.02) | (.05) | (.03) | (.03) | (.03) |
| R ² | 0.40 | 0.42 | 0.56 | 0.25 | 0.40 | 0.53 | 0.63 | 0.36 | 0.09 | 0.26 | 0.34 |

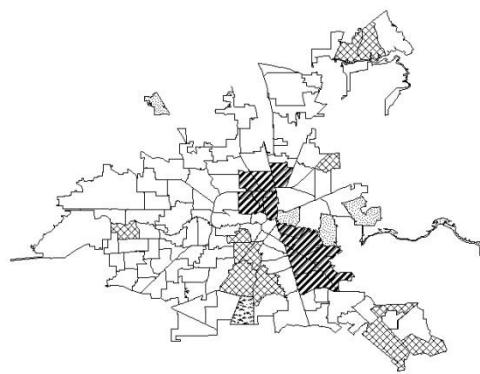
Note: Standardized regression coefficients and standard errors are reported in brackets and parentheses respectively; STOP# = number of stops, INVST = % of investigatory stops, ARRST = % of arrests, CONST = % of consent searches, PROB = % of probable cause searches, FELON = % of felony charges, RELS/INVST = ratio of releases to investigatory stops, SRCH/N_MOV = ratio of searches to non-moving traffic stops, SRCH/MOV = ratio of searches to moving traffic stops, CONTR/SRCH = ratio of contraband findings to searches.; STOP#, INVST, PROB, CONTR, FELON, SRCH/N_MOV, SRCH/MOV, CONTR/SRCH, % Hispanics, resource commitment, and population are square-rooted; CONST and % blacks are natural-logged.

* *p* < .05 (two-tailed); ** *p* < .01 (two-tailed); *** *p* < .001 (two-tailed)

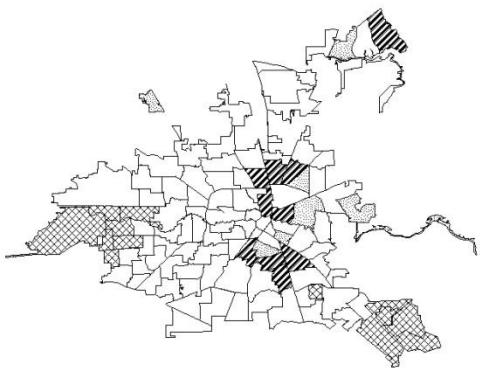
% Blacks



% Hispanics



Resource commitment

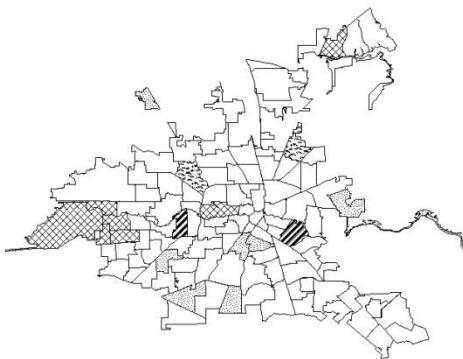


LISA Cluster Map

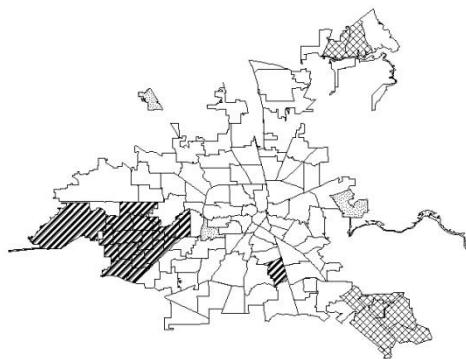
| | |
|------------------------------|-----------------|
| [White Box] | Not Significant |
| [Dark Gray Diagonal Stripes] | High-High |
| [Light Gray Cross-Hatch] | Low-Low |
| [Dotted Pattern] | Low-High |
| [Diagonal Lines] | High-Low |

Figure 1. LISA Cluster Maps of Beat Characteristics.

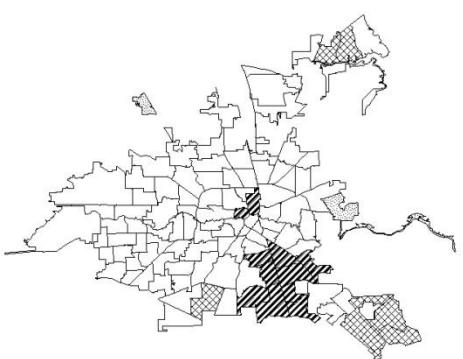
Number of stops



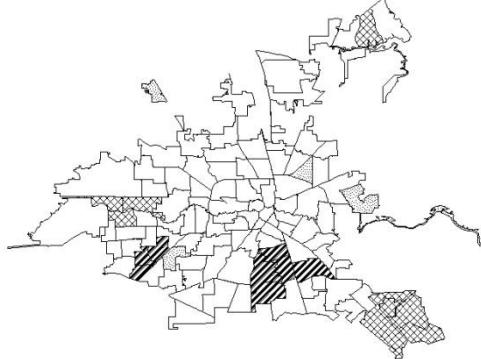
% Investigatory Stops



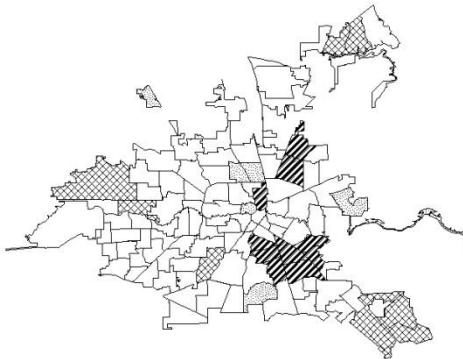
% Arrests



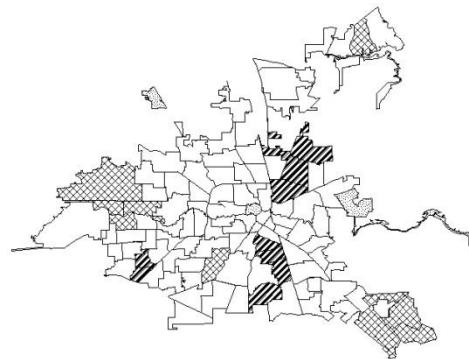
% Consent searches



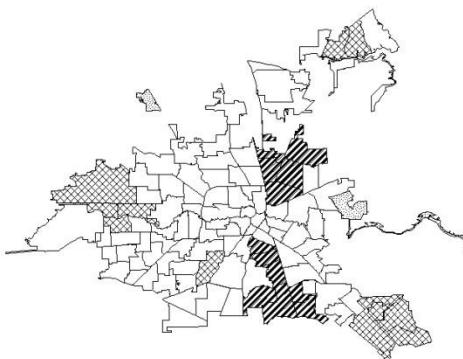
% Probable cause searches



% Contraband findings



% Felony charges



LISA Cluster Map

| | |
|--|-----------------|
| | Not Significant |
| | High-High |
| | Low-Low |
| | Low-High |
| | High-Low |

Figure 2. LISA Cluster Maps of Traffic Stops and Stop Outcomes.

¹ For other scholarly definitions of racial profiling, see Racial Profiling Data Collection Resource Center at Northeastern University (2007). Library and Archive, Glossary of Terms, at <http://www.racialprofilinganalysis.neu.edu/library/glossary.php>

² For a list of studies by year, see Racial Profiling Data Collection Resource Center at Northeastern University (2007). Library and Archives, Reports, <http://www.racialprofilinganalysis.neu.edu/library/index.php>

³ Nationwide, use of force is greater against minorities than whites, in part because of different behaviors by minority suspects and citizens in police interactions. However, differences in suspect and citizen behavior cannot explain the vast disparity in use of force by race (Robinson, 2005).

⁴ Although the driving age in Texas is 16 years old, the 15-year old population is included because the American Community Survey data lump 15 and 16 year-old populations into one age group.